ACEEE Int. J. on Signal and Image Processing , Vol. 4, No. 3, Sept 2013

An Indexing Technique Based on Feature Level Fusion of Fingerprint Features

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Abstract— **Personal identification system based on pass word and other entities are ineffective. Nowadays biometric based systems are used for human identification in almost many real time applications. The current state-of-art biometric identification focuses on accuracy and hence a good performance result in terms of response time on small scale database is achieved. But in today's real life scenario biometric database are huge and without any intelligent scheme the response time should be high, but the existing algorithms requires an exhaustive search on the database which increases proportionally when the size of the database grows. This paper addresses the problem of biometric indexing in the context of fingerprint. Indexing is a technique to reduce the number of candidate identities to be considered by the identification algorithm. The fingerprint indexing methodology projected in this work is based on a combination of Level 1, Level 2 and Level-3 fingerprint features. The result shows the fusion of level 1, level 2 and level 3 features gives better performance and good indexing rate than with any one level of fingerprint feature.**

Index Terms— **Biometrics, indexing, feature extraction, pores, ridges, minutiae, locality sensitive hashing.**

I. Introduction

In the present heterogeneous large scale database there is a necessity for fortification of data from illegitimate user. Traditionally, identification of a legitimate person was based on keys, passwords, magnetic or chip card. However, all of these can be stolen, forgotten or forged and hence password and token-based recognition systems are nowadays replaced by biometric recognition system. Even in some systems where password and token are still used, on top of it a biometric layer is added for more secure authentication. Hence there is a tremendous growth in biometric based identification system in almost all paths round the world. Biometric includes reference to the measurement, analysis, classification, science of personal recognition and verification or identification by using distinguishable biological (physiological) or behavioral trait features or characteristic of that person. Biometric identification is the process of associating an identity to the input biometric data by comparing it against the enrolled identities in a database [1].

Depending on the mode of application biometric system operate on verification or identification mode. In verification mode, the system validates a person's identity by comparing the captured biometric data with their own biometric template stored in the database; say by 1:1 matching. In identification mode, the system recognizes the person by searching the template of all the users in the database, where 1: N matching is performed. Biometric system should posses the characteristics such as: versatility, uniqueness, permanence, measurability, performance, acceptability and circumvention.

Among the various biometric traits, 'fingerprint' is proved to be a predominant and popular biometric feature for authentication and identification with a high degree of accuracy, distinctiveness and is invariant to age. The finger print has also received substantial concentration and is being effectively used in many civil and forensic applications over one hundred years. The recognition of an individual entails the comparison of the input fingerprint with the fingerprint present in the database. As the volume of database nowadays is enormous the 1 to N matching has become a very tedious and time consuming process. To downsize the search time one possible way is shrink the search space, which can be accomplished by classification i.e., separating the fingerprints into some predefined classes.

A fingerprint to be identified is then required to be compared only to the fingerprints in a particular class. Fingerprint classification can be of exclusive classification or continuous classification [2]. Exclusive classification is splitting the fingerprint database into a fixed number of classes usually say 5 classes (arch, tended arch, left loop, right loop and whorl) called the Henry's classification. The limitations in this scheme are the small number of classes and unbalanced distribution of entries in the classes. Continuous classification overcomes the limitations of exclusive classification. In continuous classification or fingerprint indexing fingerprints are not split into disjoint classes, but a numerical vector is formed by using the fingerprint features, there by forming a fingerprint index value.

This paper proposes as novel indexing technique for fingerprint based on the level-1 (ridge orientation, ridge frequency, ridge count, ridge length and, ridge curvature direction) and level-2 (minutiae and minutiae type) features. The feature set is indexed by means of Locality Sensitive Hashing (LHS). The paper is organized as follows. The basics of fingerprint and related work are described in Section 2. Level-1, Level-2 and Level-3 fingerprint features extraction are described in section 3. The proposed indexing technique based on these features is detailed in Section 4. In Section 5 experimental results are discussed. Finally, some conclusion and future works are reported in Section 6.

DOI: 01.IJSIP.4.3.1288

II. Fingerprint Basics and Related Work

A. Fingerprint Basics

A fingerprint is a pattern of interleaved ridges and valleys which run in parallel on the surface of the finger. Fingerprints mature during seven months of fetus maturity. A fingerprint does not later or changes throughout the life time of a person and even after the death of a person it can be used for identification. Fingerprints are unique, immutable and a single rolled fingerprint may have as many as 100 or more identification points. The matchlessness of a fingerprint can be indomitable by the pattern of ridges and furrows as well as the minutiae points. Because of complex distortion among the different impression of the same finger, fingerprint is still a challenging problem.

Fingerprint pattern are recognized based on Level 1, Level 2 and Level 3. The Level 1 or global features are the ridges. A ridge is defined as a single curved segment, and a valley is defined as the region between two adjacent ridges. The width of ridges in the fingerprint diverges from 30 µm to 100 µm. The length of the ridges (as cycle) is more or less 500 µm. The ridges are classified based on the singular regions, core, loop, delta and whorl. It can be further distinguished as left loop, right loop, arch, tended arch. The identification based on the global feature rely on 'core point' which is defined by Henry as the north most point of the innermost ridge line. It is not necessary for all fingerprints to possess a core point. The distinctiveness of these features is not enough for classification or indexing and hence the external features such as fingerprint orientation, shape, frequency are also considered.

The Level 2 or the local features are the minutiae. Minutia is defined based on various ways the ridges flow either continuous or discontinuous. Each minutia is represented by the x and y coordinates and the angle between the tangent to the ridge line at the minutia position and the horizontal axis. There are about 150 minutiae details in a complete rolled fingerprint among them mainly used features are ridge ending, bifurcation, trifurcation and crossover. Besides this classification it also has lake, spur, dot, and island and so on. These features are more distinctive, stable and are used in most of the indexing approach and proved to more efficient.

The Level 3 or very-fine level features are the finer details extracted from the fingerprint. They are mainly concerned with dimensions of the ridges like: width, shape, curvature, edge contours dots, and incipient ridges. Despite of its more distinctiveness than the other two levels it requires a high resolution scanner of 1000 dpi.

B. Related Work

The fingerprint matching relies on the features of the fingerprint and is classified as correlation-based fingerprint matching, minutiae-based fingerprint matching and non-minutiae based matching. In correlation-based matching the similarity measures are found and the spatial relation is found between the query image and templates stored in the database. The minutiae based technique finds alignment of the two fingerprint images. The non-minutiae based matching technique depends on level-3 features such as ridge shapes, texture formation, singularities and so on.

Fingerprint Matching Techniques

1) Correlation-Based Matching Techniques:

Fingerprints matching based on the ridge lines is proposed [3]. The characteristic used for fingerprints matching is the ridge line that joins the minutia point with the connected ridge point. A quadrilateral sets is used to evaluate the transformation of two ridge lines. Later based on the graph matching is developed to check the alignment of the two ridge lines. From the above two steps a final score is obtained and based on this matching is performed. Experiments show that the proposed algorithm is effective than the existing method.

Based on the local ridge similarity the matching of fingerprint is proposed. In this the approach local rotation angel are taken from the ridge points. After calculating the templates by using least square method, the optimal local rotation angle is obtained. A match score is calculated by analysing minutiae set. The experiment is conducted using FVC2002 DB3 and result is effective when compared with the existing conventional ridges-based methods.

A fingerprint matching technique using ridges based on hidden markov model is proposed. This method uses the ridge orientation in the region of the reference point of recorded fingerprint. Initially, fingerprint images are aligned based on a reference point. Then the ridge orientation field in the region of this point is applied to the HMM based on a topology. This topology offers many advantages such as simplicity, flexibility and generality. For estimating this matching method, an artificial continuous classification applied on FVC2000 DB2_A.

A segmentation process based on ridge search is proposed. The ridge coherence and the ridge distance variance of fingerprints are determined through ridge search. Based on this measure the matching between the input query image and template is compared and the matching is found. The Equal Error Rate (EER) is used to evaluate the performance of this method on the publicly available databases FVC2000 DB3, FVC2004 DB2 and DB4. The method has proved to more efficient when compared to the traditional method.

2) Minutiae Based Matching Techniques:

The local orientation feature and topological structure of the minutiae is considered for matching in [4]. In this method the matching is done at three stages. Initially the minutiae points are compared between the template and query image by calculating the similarities of local orientation feature and topological structure. In the next step the top pairs are taken for matching based on the reference minutiae points. In the last step a match score is generated. The method is tested is FVC2002 and gives a good matching results.

The fingerprint matching based on optimal global minutiae set using genetic algorithm is proposed. An initial set is created with local minutiae for matching. Later by applying

DOI: 01.IJSIP.4.3.1288

the genetic operator and the global search functionality a fitness function is derived. Using this function the near optimal minutiae point are identified and based on this matching is performed with input query image. The algorithm is assessed on FVC2002 database and the result is proved to be more exact and faster than the existing methods.

A fingerprint matching based on the minutia and the binary relation between minutiae is proposed. The fingerprint is represented with the help of a graph, where the comprehensive minutiae act as the vertex set and the local binary minutia relations acts the edge set. The transformation-invariant and transformation-variant features are extracted from the binary relation. The transformation-invariant features are used to estimate the local matching probability, and the transformation-variant features are used to represent the fingerprint rotation transformation. Ultimately, the fingerprint matching is carried out with the variable bounded box and iterative methods.

Minutiae based fingerprint matching using minutia global transformation between two different fingerprints is proposed. The Local Patch Descriptor (LPD) and the Geometrical Configuration Descriptor (GCD) are two descriptors used to match the finger print. A small set of matched pairs between two different fingerprints are established based on these two minutia descriptors. Along with this a global transformation is found by using RANSAC algorithm. The matching result is calculated using global transformation. An experimental result shows good matching accuracy.

The minutiae and the curvature of ridge are used to match the fingerprint. Three categories of critical factor were defined to explain the pattern of fingerprint. According to the factors the relationship between the minutiae and the neighbourhood ridges are used for comparison. The deciding score is done based on the result of the matching done previously in the step match. The experimental result shows a high matching rate.

Using an elaborate combination of minutiae and curvature maps of the fingerprint images is proposed. Initially, curvature calculation based on fingerprint orientation fields is done from fingerprint images. In the next stage, a curvature-based minutia specifier, which appears to be a circular pattern, is set up by taking sampling around the minutia. Thirdly, a measurement on similarity degree between two minutia specifiers is computed. A validation algorithm is done based on the reliable and maximum curvature points to increase the accuracy. The fingerprint matching algorithm is tested on FVC2002. The results demonstrate the good performance and high accuracy rate.

Fingerprint matching algorithm based on global minutiae and invariant moments is proposed. In this method combination of other discriminatory features are included in order to effectively strengthen the performance of the matching. From the fingerprint image a reference point based on the minutiae is determined. Later, keeping the reference point the fingerprint template is aligned. Based on the aligned fingerprints, combined features are constructed from all the minutiae and their invariant moments, and a global matching algorithm is proposed to match the template and input fingerprint. The experimental result illustrates a higher performance result with FVC2004 databases.

An extend minutiae based methods to incorporate local image information is proposed. This method uses local minutiae information. The overall minutiae distribution pattern among the two fingerprints is characterized by the initial minutiae which are based on neighbourhoods of matched minutiae. FVC2002 DB1 and DB3 databases are used to evaluate the proposed method. Experimental result shows the improvement when combining minutiae matching scores with mutual information

Fingerprint matching based on local orientation of the minutiae is proposed. The matching process under goes three stages. In stage one, local orientation structures is matched to find the similarity between the orientation structures around the minutiae point. During stage two, the structure of the local minutiae comparison is evaluated. In the last stage, the matching pair sets are created using global minutia structures and the local minutia structure, which evaluated the global similarity. Then, similarity score is obtained using the three stages. Experiments are performed on four databases of FVC2002 and the matching result is high.

Minutiae based fingerprint matching which relies on minutiae-centered circular regions is proposed. Along with the minutiae a secondary feature is used to form a circular region around the minutiae. A small fingerprint region is taken and from this region the minutiae points are used for matching. The method uses a large number of minutiae for matching. Since only a small region is considered it is more lenient to any distortion in the input image.

Fingerprint matching is based on some five closest neighbours of one single minutia. The single minutia chosen is called as centre minutia point. A verification of minutia is done based on these surrounding neighbours of the centre minutia point. This approach is divided into two phases. The first phase performs initial filtration. The second stage does special matching decisive factor that integrates fuzzy to select final minutiae for matching score calculation. The method of selecting center point for second stage is also adopted. This algorithm is able to perform well for feature invariant like translation, rotation and enlarge fingerprints and does not necessitate any procedure for alignment before matching. Experimental results show that algorithm is efficient and reliable.

A novel fingerprint matching algorithm using both ridge features and minutiae feature to increase the matching performance is proposed using breath-first search. The ridge features are compared based on: ridge count, ridge length, ridge curvature direction, and ridge type. The minutiae features are compared based on: minutiae type, orientation, and position. A mapping method using a breadth-first search is proposed to detect the matched minutiae pairs incrementally. Later, the maximum score is computed and used as the final matching score of two fingerprints. FVC2002 and FVC2004 are used for experiments. The method accomplished

higher matching rate.

The global topological features are used for fingerprint matching after that, a solution for the inverse model is presented. This allows protecting data fidelity in the existing segments while exploring missing structures. Later the omitted orientation structures based on some a priori knowledge is considered.

Fingerprint matching is based on the graphical structure derived from the minutiae and local structure is proposed. A feature vector is built from the neighbourhood minutiae points which are used to easily locate the actual minutiae point. Neighbouring features of the minutiae point provides the sequence of secondary minutiae which directly join with the central minutiae on topology. The experiments are carried out using FVC2002, and the results verified the effectiveness of the proposed approach.

A Combination of minutiae with local neighbour flow pattern of the ridge is proposed. The features around the minutiae are used for local alignment and matching of the minutiae. This method achieves better alignment of local bending energy and is used for comparing two minutiae points. The result has proved good performance and improvement on fingerprint identification.

A multilevel fingerprint identification based on global features is used. In this method the input fingerprint image is decomposed into sub-regions based on the global features. Thereafter a multilevel feature vector template is prepared using the local, neighbourhood and global features of the fingerprint image. This method relies more on the orientation field and singular point. Even though the method takes into consideration the minutiae points but during matching it does not depend on the minutiae points. The method has been compared with publicly available six databases and the matching time is only 0.23 sec.

The conventional minutiae based method for fingerprint identification is over come by a novel method using minutiae handedness. As in the traditional method the minutiae point is identified. The minutiae points are kept as reference points and as additional information, minutiae handedness is included to identify the correct points. During the matching process along with the minutiae point the orientation fields are also considered for assessment. The proposed method is tested with eight data sets and the result shows the higher rate of accuracy.

3) Non-Minutiae Based Matching Techniques:

The major level 3 feature such as dots and incipient, based on local phase symmetry are used for matching the fingerprint in [5] and demonstrate their effectiveness in partial print matching. Since dots and incipient can be easily encoded by forensic examiners, we believe the results of this research will have benefits to Next Generation Identification (NGI) systems.

A hierarchical matching system that makes use of features at all the three levels extracted from 1,000 dpi fingerprint scans is proposed. The Level 3 features are taken out using Gabor filters and wavelet transform. Using the Iterative Closest Point (ICP) algorithm the features are matched. The experiments show that level 3 features carry significant discriminatory information. The experimental result has shown a relative reduction of the EER of the matching system when level 3 features.

The Level 3 features on fingerprints have demonstrated to be discriminative features and are engaged in automatic fingerprint identification systems in current identification systems. The sweat pores on the fingerprint is used for matching with template. Based on the Local Binary Pattern (LBP) feature the pores are matched. The experimental results are tested on NIST database and are evaluated with the help of Equal Error Rate. The method has yielded a low Equal Error Rate with high accuracy.

Level 3 fingerprint features and the ridge features from fingerprint are used for matching the fingerprint images. Along with matching liveness detection is also performed. The level 3 features are detected using Wavelet based techniques. Delaunay triangulation based alignment and matching of the fingerprints is performed. The experiment is tested on self-data with a high resolution data of 686 dpi and obtained a low Equal Error Rate.

Fingerprint Indexing Techniques

In biometric template there is no natural order by which one can sort the biometric records. In indexing approach each data is assigned a index value and this value is used to identify an imposter. The need for an indexing scheme in large scale biometric system are: (1) searching the database to indentify a correct person in less time and (2) as the db grows there are more changes of false accept error [6]. In this section we review the finger print indexing and iris indexing techniques. Fingerprint indexing can be classified based on their features: (1) Global Feature (2) Local Ridge Line Orientation (3) Minutiae and (4) Other Features.

1) Based on Minutia:

Cappelli et al [7] proposed a hash-based indexing method to speed up fingerprint identification in large databases. The minutiae cylinder code (MCC) encodes the neighbor of each minutia point into a fixed length bit vector. The bit vector is indexed by means of Locality-Sensitive Hashing (LSH). Each minutiae is a triplet $m = \{x_m, y_m, {}_m\}$ where x_m & y_m are minutia location and ${}_m$ is the minutia direction. A binary vector set v_i us created using MCC from the given template and for each vector v_j the hashing function is applied. During the creation of the index any binary vector v_j of each template t_i is given as input to all the hash function and the pair(i,j) identifies t_i. The similarity between two templates is counted by the number of collision of each pair of binary vectors. The binary vector obtained with MCC has only a few 1 bits then it is more likely to contain a larger no of pairs. This scheme has been designed relying on Minutiae Cylinder-Code (MCC), which proved to be very effective in mapping a minutiae-based representation into a set of fixed-length transformation-invariant binary vectors. Experimentations have been carried out to compare the proposed approach against 15 existing methods over all the benchmarks typically used for fingerprint indexing. In spite of the smaller set of features used (top

DOI: 01.IJSIP.4.3.1288

performing methods usually combine more features), the new approach outperforms existing ones in almost all of the cases.

Mansukhani, P et al proposed a new indexing method for fingerprint templates consisting of a set of minutia points is considered. One large index tree is constructed and the enrolled templates are represented by the leaves of the tree. The branches in the index tree correspond to different local configurations of minutia points. Searching the index tree entails extracting local minutia neighbourhoods of the test fingerprint and matching them against tree nodes. Therefore, the search time does not depend on the number of enrolled fingerprint templates, but only on the index tree configuration. This framework can be adapted for different tree-building parameters (feature sets, indexing levels, bin boundaries) according to user requirements and different enrolment and searching techniques can be applied to improve accuracy. Testing has been done with a datasize of 6,400 users and the time taken per user remains constant as even when the datasize was 100. The experiments confirm the ability of the proposed algorithm to find correct matches in the database and the minimum search time requirements.

R. Singh et al in their method used level-2 minutiae features and level-3 pore feature as the parameter for indexing. A Delaunay triangle using the minutia is formed. With the given n minutiae point a voronoi diagram is drawn which decomposes the minutiae points into regions and hen the Delaunay triangulation is joined by minutiae co-ordinates present in the neighbourhood voronoi regions. Each triangle in Delaunay triangulation is used as minutiae triplets. The identification performance is further improved by incorporating Dempster Shafer theory based match score fusion algorithm. Experimental results on a high resolution fingerprint database show that the proposed algorithm improves the identification performance by at least 10% compared to existing fingerprint identification algorithms.

X. Liang et al used an approach which concentrates on a more accurate fingerprint indexing algorithm that efficiently retrieves the top N possible matching candidates from a huge database. This method is based on minutia neighbourhood structure (this minutia detail contains richer minutia information) and a more stable triangulation algorithm (low-order Delaunay triangles, consisting of order 0 and 1 Delaunay triangles), which are both insensitive to fingerprint distortion. The indexing features include minutia detail and attributes of low-order Delaunay triangle (its handedness, angles, maximum edge, and related angles between orientation field and edges). Experiments on databases FVC2002 and FVC2004 show that the proposed algorithm considerably narrows down the search space in fingerprint databases and is stable for various fingerprints. It is also compared it with other indexing approaches, and the results show that the algorithm has better performance, especially on fingerprints with distortion.

B. Bhanu and X. Tan approach is based on triplets of minutiae for identifying fingerprints under translation, rotation, scale, shear, occlusion, and clutter. In this a model-based approach, which retrieves correct hypotheses using novel features of triangles formed by the triplets of minutiae as the basic representation unit. The triangle features that are used are its angles, handedness, type, direction, and maximum side. Geometric constraints based on other characteristics of minutiae are used to eliminate false correspondences. Experimental results on live-scan fingerprint images of varying quality and NIST special database 4 (NIST-4) shows that the indexing approach efficiently narrows down the number of candidate hypotheses in the presence of translation, rotation, scale, shear, occlusion, and clutter. Performance of the approach with another prominent indexing approach shows that the approach is better for both the live scan database and the ink based database NIST-4.

J. De Boer et al approach is based on three multiple fingerprint features: the registered directional field estimate, Finger Code and minutiae triplets. It is shown that indexing schemes that are based on these features, are able to search a database more effectively than a simple linear scan. The indexing scheme is constructed that is based on advanced methods of combining these features. It is shown that this scheme results in a considerably better performance than the schemes that are based on the individual features or on more naive methods of combining the features, thus allowing much larger fingerprint databases to be searched. The result compared to a simple linear search, allows the size of databases to be 100 times as large, while maintaining the same FAR and FRR.

2) Based on ridge orientation and frequency:

Heeseung Choi et al [8] proposed a method which is based on vector and scalar features, obtained from ridge-line orientations and frequencies. The vector and scalar features are chosen as local orientation and frequencies are extracted by matching algorithm and the average frequency can improve indexing performance. The scalar value and vector element can be stored in a single byte with a negligible loss of accuracy. The two scalar features derived from the orientation and frequency image, the average frequency is calculated as

$$\Delta_{\theta}=\frac{\sum_{y=1}^{h=1}\sum_{x=1}^{w}(S_{x,y}\cdot S_{x,y+1}\ \ .d\theta\ (\theta_{x,y},\theta_{x,y+1}\ ))}{\sum_{y=1}^{h-1}\sum_{x=1}^{w}(S_{x,y}\cdot S_{x,y+1}\ \ )}$$

where w and h are the width and height of the orientation image. Based on the value the finger print image is sorted and stored. Owing to a carefully designed set of features and ad-hoc score measures, this approach has proved very efficient: once the features have been extracted, searching for a fingerprint requires just 2.3 ms over the NIST DB14 data set. Scalability experiments on a data set containing one million synthetic fingerprints achieved very good results: on a standard PC, indexing one million fingerprints requires 709 MB of memory, and a fingerprint search over such a large data set takes less than 1 s. Finally, it is worth noting that the efficiency of the proposed approach may be further increased by adopting spatial data structures or ad-hoc clustering techniques to narrow down the number of score measure computations. This method was tested over six publicly

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available data sets. Furthermore, it can scale to large databases without losing accuracy: on a standard PC, a search over one million fingerprints takes less than 1 s.

J. Feng and A. Cai proposed an invariant-based fingerprint indexing scheme. Minutia and surrounding ridges are combined to form a substructure. The invariants describe binary relations between substructures. Since partial overlap is common in fingerprint matching, instead of using a single feature vector to characterize the relations between a pair of substructures, they use lots of local invariants, which describe the relations between sampled points in two substructures. One of the two substructures is called base substructure (BS), and the other called associated substructure (AS). From each sampled point (called BP) on each ridge (called BR) in BS, draw a line L (called scanning line) along $\alpha = \theta(BP) + \pi/2$, where $\theta(BP)$ denotes the flow direction of BP. If L intersects a ridge (AR) in AS at a point (the sampled point nearest to this point is called AP), an index is generated. Experimental results on FVC2002 database demonstrate the validity of the proposed algorithm.

3) Based on global and other features:

X. Shuai et al [9] proposes a fingerprint indexing based on scale invariant feature transformation (SFIT). SFIT features has tow advantages compared with minutiae (1) generates a large number of features over a broad range of scales and location, while the minutiae points is limited to small numbers. (2) Most minutiae point can be deducted by SFIT. With slight loss in effectiveness, they reduce the number of features generated from one fingerprint for efficiency. To cope with the uncertainty of acquisition (e.g. partialness, distortion), a composite set of features to form multiple impressions for the fingerprint representation is used. In the index construction phase, the locality-sensitive hashing (LSH) is adopted for high dimensional index construction. Experiments on database FVC2000 DB2 and FVC2002 DB1 is carried to check the efficiency of the algorithm.

J. Li et al method is based on three symmetrical filters of different orientation structures. The three kinds of symmetrical filters, which are the core type filter, the delta type filter and the parallel type filter, to map the different structures of fingerprints into three different feature spaces. These three fingerprint orientation structures have more targeted capability of capturing the specialty of the fingerprint orientation image. In this method, an assumption made is that the reference point should be available when acquiring a fingerprint image if not, the fingerprint may not include enough information to be indexed. The performance of the algorithm will also be affected by noise in the data, normalization ie the reference point and its direction as not always correctly estimated for some image and resolution when not good. Experiments conducted on the NIST database 4 shows the effectiveness of the proposed approach.

T. Liu et al proposed a method in which a continuous fingerprint indexing method based on location, direction estimation and correlation of fingerprint singular points is used. Location and direction estimation are achieved simultaneously by applying a T-shape model to directional field of fingerprint images. The T-shape model analyzes homocentric sectors around the candidate singular points to find lateral-axes and further main-axes. Then a distortion-tolerant filter of Minimum Average Correlation Energy is utilized to obtain a correlation-based similarity measure which gives the evidence of searching priority. The experiment is performed by 400-fingerprint retrieval from 10,000 templates and the mean search space is only 3.46% of the whole dataset.

4) Based on coding technique:

A. Gyaourova and A. Ross [10] proposed a method for generating index codes for fingerprint images by using a small set of pre-determined reference fingerprints. In this method, the match scores generated by comparing an input fingerprint with the reference fingerprints are subjected to a discretization function, which converts them into an index code. A search mechanism based on the Hamming distance identifies those index codes in the database that are similar to the code of the input image. The proposed technique has several advantages: it obviates the need to extract complex features from the fingerprint image; it utilizes the matcher that is already associated with a particular application. Experimental results on two fingerprint databases (NIST-4 and WVU) indicate that the proposed encoding scheme generates index codes that are well-scattered thereby allowing noisy query images to be indexed correctly.

The study on related work using fingerprint as a parameter for indexing portraits a lot for organizing the fingerprint in the database. From the assessment on ridge features and minutiae feature is clear that indexing based on the combination of these features can yield a better indexing result.

III. Proposed Fingerprint Feature Extraction

The proposed work is based on level-1, level-2 and level-3 fingerprint features. The overall fingerprint feature extraction is divided into pre-processing stage and post-processing stage. The various stages in fingerprint feature extraction are depicted in fig 1. During the pre-processing stage the input foreground fingerprint image is separated from the background image. This process is called as segmentation. The key objective of any segmentation algorithm is to discard the background from the foreground of the input image as the fingerprint are striated patterns and cannot be efficiently isolated from the background.

In the proposed method Harris corner detection scheme is used for segmentation [11]. Harris corner detector is an improvement of Moravec's corner detector which was originally developed for motion tracking. Harris corner uses Gaussian function

$$w(x, y) = \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

to reduce noisy response due to binary window function instead of shifted patches. The average intensity changes in direction, is expressed in bilinear form and describes a point in terms of Eigenvalues. It is invariant to rotation but non-invariant to scaling. The ridge orientation and ridge frequency are estimated from the segmented image. The local orientation

DOI: 01.IJSIP.4.3.1288

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feature is extracted using the gradient based approach. The feature is estimated at every 16 pixels along the horizontal and vertical axis. Once this process is completed the Gabor filter is used to obtain the skeletonized image. The skeletonized image is a 1 pixel wide digital skeleton of ridges. From the skeletonized image the proposed method extracts the level-1, level-2 and level-3 features. The overall block diagram is shown in fig 2.

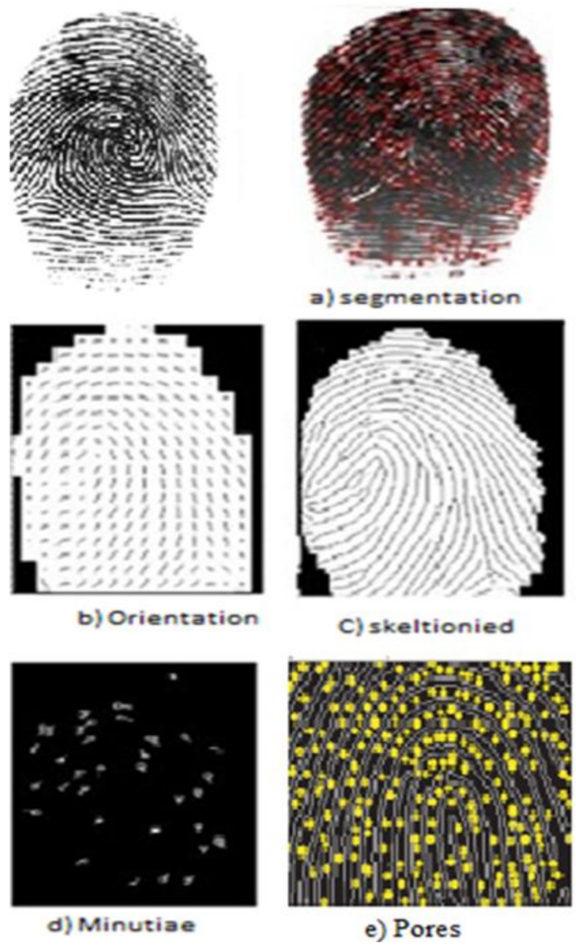

Fig. 1. Stages in Fingerprint Feature Extraction

Level-1 Ridge Feature Extraction: In the proposed method the extracted ridge features are:

- ridge orientation (ro)
- ridge frequency (rf)
- ridge count (rc)
- ridge length (rl)

Ridge orientation is defined at a point (x, y) is the angle Θ_{xy} at the fingerprint ridges crossing through an arbitrary small neighbourhood centered at (x, y). The gradient-based approach [12] is used to extract the local ridge orientation. The gradient $\nabla(x,y)$ at point [x, y] of P is a two dimensional vector $[\nabla_x(x,y), \nabla_y(x,y)]$, where and components are the derivatives of P at [x, y] in x and y direction.

Local ridge frequency is the number of ridges per unit length along a hypothetical segment orthogonal to the local ridge orientation. The local ridge frequency is estimated based on [13] where the average numbers of pixels between two consecutive peaks are counted.

Ridge count is the number of ridge lines between any two points in a fingerprint. Ridge count is invariant to geometric transformation. Ridge length is measured as the distance on horizontal axis from the intersection of the vertical and horizontal axis to a minutia. The length of the ridges (as cycle) is more or less 500 µm.

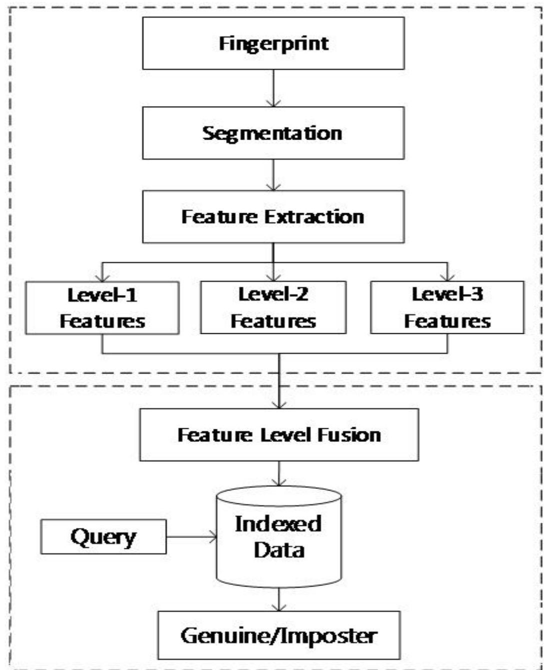

Fig. 2. Block diagram of the proposed system

Level-2 Minutiae Extraction: Minutiae points are detected from the skeletonized image. Each minutia is a set of x and y coordinates and the angle between the tangent to the ridge line at the minutia position and the horizontal axis. In the proposed work the minutia type along with minutia point is considered. The type of minutiae is determined as follows based on the ridge flow. To determine the minutia type the end point of each ridge is identified as follows:

- End point: if an ridge line end at any point
- Bifurcation: if a ridge line diverge into two branches at any point
- Trifurcation : if a ridge line diverges into three branches at any point
- Crossover: if a two ridge lines intersects at any point and continue to flow

In the proposed method we have adapted the direct gray scale minutiae extraction in [14]. In their method given an initial point and its direction along the ridge line a new point is computed by moving µ pixels. This method is continued until the stop criterion is true and at this stage we obtain the minutiae set M={x, y, Ÿ, type}. Based on the fingerprint features extracted the indexing feature vector is determined as ridge orientation, ridge frequency, ridge count, ridge length, ridge curvature direction, minutiae and minutiae type.

Level-3 Pores Extraction: Pores are smaller points where the diameter is small than the ridge width which emanate perspiration. The pores lie on the ridge line. Depending upon

DOI: 01.IJSIP.4.3.1288

the position of the pore it is classified as open pores and close pores. The close pore lies inside the ridge line. The open pores lies partially on the ridge and partially on the valley. The position of the pore and the density of the pore have more distinctiveness. The distance between the consecutive two pores is relatively closer. A fingerprint consist around 1400 pores. In the proposed work the pores are calculated from the skeletonized image.

IV. Proposed Indexing Technique

The biometric template has no natural order by which one can sort the biometric records. To index the fingerprint biometric data each data is assigned with an index value generated based on the features extracted from the fingerprint and this value is used to identify an imposter. In the proposed method we have used Locality-Sensitive Hashing (LSH) [15]. LSH considers the locality of the points so that the nearby points remain closer instead of finding exact match as in other conventional hashing techniques.

LSH is used to perform dimension reduction in a high dimensional data. The LSH is a scalar projection denoted by $h(\overrightarrow{v}) = \vec{v}.\vec{x}$ and defined as:

$$h^{x,b}(\overrightarrow{v}) = \left\lfloor \frac{\vec{x}.\ \vec{v} + b}{w} \right\rfloor$$

where $\vec{v}$ denotes a point in a high dimensional space, is a vector component at random from Gaussian distribution, w is the width of each quantization bin and b is a random variable uniformly distributed between 0 and w. The scalar projection is quantized into a set of hash bins in order to make all nearby points to fall into the same bin.

The points that are close together should posses the following properties.

- For any point p and q in Rd which are close to each other then there is a probability that P1 fall into same bucket such that

  $$P_H[h(p) = h(q)] \geq P_1 \text{for} \|p - q\| \leq R_1$$

- For any point p and q in Rd which are away from each other then there is a probability that P2 < P1 and that they fall into same bucket such that

  $$P_H[h(p) = h(q)] \leq P_2 \text{for} \|p - q\| \geq cR_1 = R_2$$

The LHS procedure is as follows:

- Define a family of hash function S{g} and $H = \{i_1, i_2, \dots . i_n\} \subseteq \{1,2, \dots \dots n\}$.
- Construct n hash function randomly choosing n subsets H1, H2,..... Hn and a index table consist of n hash table H1, H2,..... Hn.
- Each vector v is placed into bucket $fH_k(v)$ of each hash table H_k for k = 1 to n.
- For each query vector perform a similarity search and nearby vectors are retrieved as list of matches from the corresponding buckets.
- Calculate the similarity score using hamming distance.

V. Experimental Results

The proposed fingerprint indexing method is experimented using the FVC2002 DB1_A. The image size is 388 x 374 and resolution is 500 dpi. The database consists of 100 fingers and each finger consists of 8 impressions. The performance of any biometric system is evaluated in terms of False Acceptance Rate (FAR) and False Reject Rate (FRR).

The system was experimented at two stages as a monomodal system and then the proposed feature level fusion was implemented in MATLAB. The experimented results are shown in table 1.

Table I. Comparison of the proposed system

Traits	FAR	FRR
Level-1 features	0.58 %	6.2 %
Level-2 features	0.63 %	8.4 %
Level-3 features	0.72 %	8.2 %
Proposed method	0.1 %	3.2 %

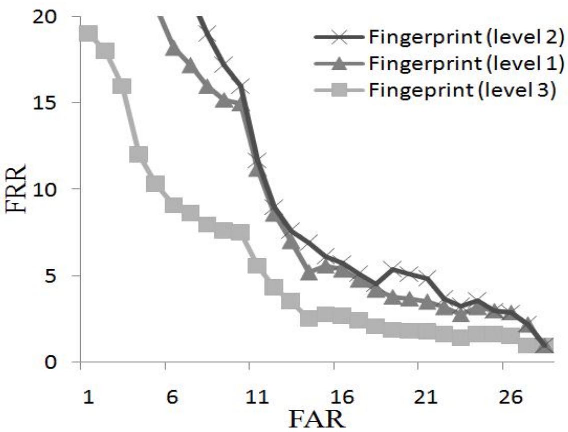

Fig. 3. Performance result with level 1, level 2 and level 3 fingerprint feature

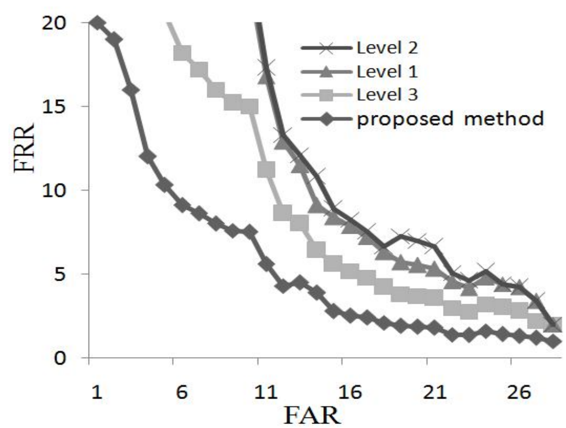

Fig. 4. Performance result of the proposed system

The fig. 3 shows the performance the identification system with fingerprint level 1, level 2 and level 3 feature extractions. It is analyzed from the experimental results that system gives better performance than with a single biometric feature as shown in the fig 4.

The performances of the indexing technique are generally evaluated based on penetration rate, hit rate, miss rate and redundancy rate.

- Penetration rate (P_r): The portion or fraction of the total database retrieved by the system for user identity.

$$P_r = \frac{1}{X}\sum_{i=1}^{x}\frac{k_i}{N}\times 100$$

Where X is the total number of query images correctly identified and K_i is the number of images retrieved per query and N is the database size.

- Hit rate (H_r): Indicates the possibility that the correct identity belongs to at least one of the retrieved subset images.

$$H_r = \left(\frac{X}{L}\right)\times 100\%$$

Where X is the number of times a query corresponding identity is occurred at top best match and L is the total no of attempts.

- Miss rate (M_r): indicates the possibility that the correct identity belongs to none of the retrieved type.

$$M_r = 100- H_r$$

The algorithm is evaluated with the hit rate and penetration rate. The proposed algorithm is first evaluated with level-1 features and compared with the proposed method which is shown in fig.5.

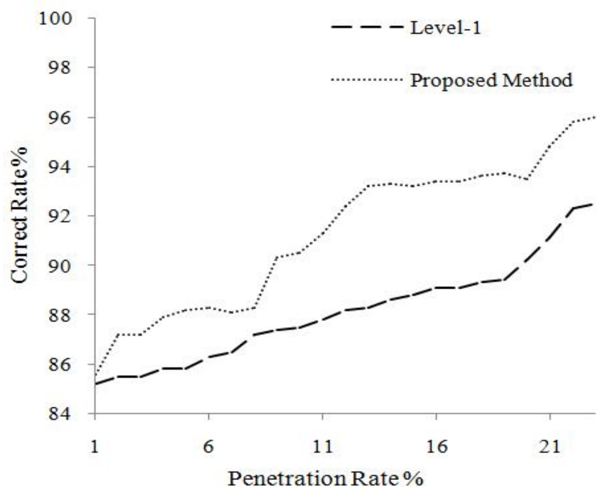

Fig. 5. Correct Rate versus Penetration Rate for the Level-1 and proposed method

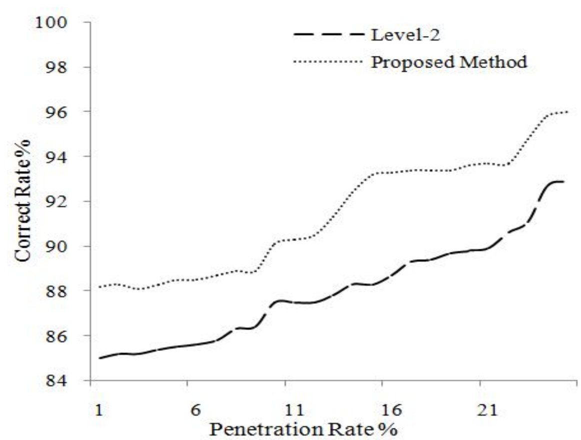

Fig. 6. Correct Rate versus Penetration Rate for the Level-2 and proposed method

As next stage of comparison it is evaluated with level 2 and level 3 features and proposed method as shown in fig. 6 and fig 7 respectively.

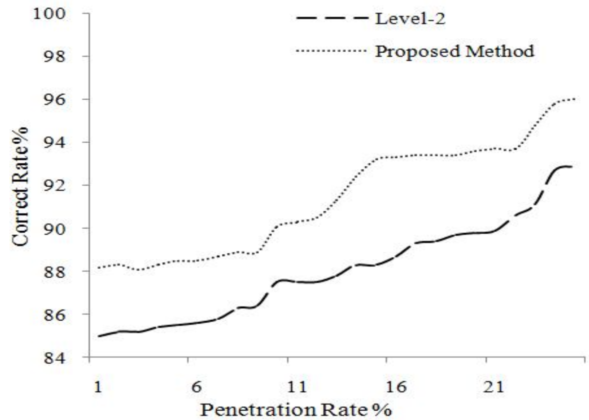

Fig. 7. Correct Rate versus Penetration Rate for the Level-3 and proposed method

VI. Conclusion

In this paper we proposed a novel fingerprint indexing technique which is the current state-of-art. An efficient fingerprint feature level fusion and an indexing algorithm is proposed based on

- Level-1 : ridge orientation, ridge frequency, ridge count and ridge length
- Level-2 : minutiae and minutiae type
- Level-3 : pores

Even though level-1, level-2 and level-3 features were able to index the data, the result projected that the combination of level-1, level -2 and level-3 gives better indexing. The proposed work was indexed using LSH. LSH considers the locality of the points so that the nearby points remain closer instead of finding exact match as in other conventional hashing techniques.

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